Proceedings of the 3rd Annual
IEEE Conference on Automation Science and Engineering
Scottsdale, AZ, USA, Sept 22-25, 2007

A Type-2 Fuzzy Planner with Semi Qualitative World Model for Robocup Domain

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Abstract— **The inherent uncertainty present in robotics in general and Robocup in particular demands the use of probabilistic methods. With its fuzzy constructs, Fuzzy Logic has been used as a solution for the current problems of robotics including uncertainty. Extending the use of Fuzzy Logic with Type-2 systems and high level world models should present new solutions to the robotics domain.**

I. Introduction

In the Four Legged League[1] of the Robocup[2] the planner module acts as the personal coach of the robot. A planner should be able to generate the right planning decision, given a state of the world model and a state of the robot. The term *decision* generally refers to selecting the most appropriate role-action pair, where the *role* of the robot defines the its current goal and the *action* defines the robot's behavior.

Currently one of the unresolved tasks of robotics is achieving a robust planner. It is possible to code sensible role-action pairs using current infrastructures. However there is no golden standard solution to the question of "how do we associate the role-action pairs sensibly?". Several methods have been developed, some of which are: The subsumption architecture, where higher level goals subsume lower level goals [7]; the context depended architecture, where a fuzzy method is used to choose the appropriate action [4] [3] [5], and the widely used method of finite state machines (FSM), where the robot alternates between a number of previously described FSM according to some predefined set of rules.

In this paper we will introduce an attempt to present a solution to the not fully resolved question of fusing actions together, using a fuzzy type-2 approach with the added flavor of semi qualitative world model.

II. Existing Planners

A. Subsumption

Subsumption architecture [7] is a possible answer for the above mentioned problem, however the layered structure of the architecture is not flexible enough to allow coordination multiple behaviors. The layers are only used to provide a hierarchy between behaviors, where lower level behaviors are subsumed by higher level behaviors when necessary. The current paradigm of Probabilistic Robotics suggests us a more integrated approach, also trying to handle the huge amount of uncertainty in the environment.

B. Context Dependent Blending

Context Dependent Blending (CDB) [5] is another inspiring candidate answer, described as follows:

1) Each behavior generates preferences from the perspective of its goal.
2) Each behavior has a context of activation, representing the situations where is should be used.
3) The preferences of all behaviors, weighted by the truth value of their contexts, are fused to form a collective preference.
4) One command is chosen from this collective preference.

CDB can constitute a complete answer to the planning problem of the Robocup domain with the implementation of fuzzy methods. CDB includes the basic intuition behind an integrated planner, where all behaviors are active simultaneously. This enables the planner to judge the current situation using a wider spectrum of possibilities and to consequently act more reasonably.

However, CDB does not address the uncertainty of the environment. It may be argued that, what makes robotics interesting is the huge amount of uncertainty in the environment. There are numerous causes of this uncertainty including, sensor limitations, effector/actuator limitations and partially observable robot and environment. Each input to the decision process generally contains huge amount of noise. Currently, robotics researchers are trying to cope with this extreme amount of noise via probabilistic approaches.

Type-2 fuzzy logic brings a measure of uncertainty to the fuzzy logic systems. Given the inherent uncertainty in robotics environments, Type-2 fuzzy logic becomes a promising candidate solution. To bring type-2 fuzzy logic into the scene, we might use a CDB architecture extended with type-2 fuzzy logic to handle this uncertainty. Employing type-2 fuzzy logic as a means of robotics control has been shown to be successful under some conditions[10] [11]. In these demonstrations the experiment application is to navigate a robot under relatively controlled environments compared to Robocup's rather more dynamic and fast paced soccer matches.

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C. Hierarchical Type-2 Fuzzy Logic Control

In [10] a Hierarchical Type-2 Fuzzy Logic Control (HFCL) is described, where interval type-2 fuzzy set representation is used in low level (right and left edge following, obstacle avoidance, goal seeking) and high level (coordination of behaviors above) fuzzy controllers, and thus the method is called HFCL due to the separation of low level and high level tasks.

While such coordination suffice for a single robot following a path, in Robocup domain, the robot soccer players generally need to accomplish much more in terms of localization, behavior choosing, team formation, processing multiple objects using mainly visual input, in a more dynamic environment.

One of the problems of such an environment is the increased uncertainty due to the great number of highly dynamic elements. Type-2 fuzzy sets might be used to overcome this uncertainty, therefore using only interval type-2 fuzzy sets, as in [10], would be disregarding a big portion of type-2 fuzzy logic.

III. Proposed Planner Architecture

The planner described in this paper uses a layered architecture similar to the planner of the Cerberus Robocup Team [8], where plans (named roles in [8]) and behaviors (named actions in [8]) are separate entities. At the highest level plans (roles) define highest level goals, namely type of the player the robot represents such as an attacker, a defender or a goalie. Behaviors (actions) define lower level physical actions such as searching for the ball, grabbing the ball or kicking the ball. The separation of the roles and actions provide a layered architecture, which enables us to define a robot soccer player.

As stated above, coding reasonable plans and actions is possible at the current stage of development, however it is still problematic to combine these entities in a reasonable fashion under the official Robocup soccer match conditions. Our planner aims to propose a solution to this problem.

We hereby present a planner architecture, where the planner fuses the results of all plans. Plans fuse results of their respective behaviors. Individual plans can use all the available behaviors to describe its plan in a finite state machine fashion. The suggested novel improvement is the method used in fusing of the respective results obtained at all levels using type-2 fuzzy logic in the planner of a robot in the 4 legged league of the Robocup. Here is the general structure of the proposed extension to CDB:

1) Each plan generates preferences for the control output from the perspective of its goal using its behaviors.
2) Each behavior has a context of activation and an associated activation distribution, respectively, representing the situations *when* this behavior should be used and probabilistic distribution describing *how* this behavior should be used in the integration process.
3) The preferences of all behaviors, weighted by the truth value of their contexts, are fused according to their activation distributions to form a collective preference.
4) All preferences of all the plans are fused together to produce the final control output using fuzzy methods.

In terms of type-2 fuzzy logic, the context of activation represents the *primary membership* function and the associated activation distribution represents the *secondary membership* according to their definitions in [12].

The main motivation of this approach is to capture at least some of the uncertainty of the environment using the secondary membership functions of the type-2 fuzzy system. Since the main source of uncertainty lies in recognizing what is going on in the environment, and implications of this uncertainty performing wrong behaviors at wrong times; adding a touch of uncertainty to the behavior fusion process seems to be a following idea.

IV. Semi Qualitative World Model

The planner module is located at the top of the coding hierarchy, where terms like scoring a goal, defending the goal, and obstacle avoiding are discussed, unlike the lower ends, such as the vision module, where one of the main tasks is to generate a distance measure of the object viewed on the scene. Therefore within the planner architecture, it is most sensible to think also about the world in higher level terms.

Many higher level extensions may become possible, such as a Semi Qualitative Localization Module via the use of higher level terms in the fuzzy planner. The motivation of this work lies in the fact that if we want robots to perform higher level tasks, then have to process in higher level terms to be successful. Trying to map lower level actions with higher level desires of humans should be much harder than mapping lower level actions to higher level behaviors/plans coded in robot's memory. With the interface provided by SQWM between goals set by humans and plans coded in robot's memory, generating very interesting behaviors may be possible.

Qualitative Reasoning [9] (QR) notions may be put into use at this point. In QR, qualities are given more importance than the quantities. The benefits of this idea can be demonstrated with the following application example: exact location of the player in terms of x, z, θ is not necessary for the planner, only the position of the player relative to the game is necessary. In other words if there is a ball to be cleared, planner module is not interested in how many millimeters away the ball is; what planner module uses to make its decision is a more qualitative attribute of the ball, such as distance of the ball represented as a fuzzy set with members *far*, *near*, *close*, *contact*. Lower levels of the architecture should be employed to defuzzify the decision of the planner.

Fuzzy methods provide us, an intermediate world model which might be used to exploit higher level reasoning made available by the environment. By establishing a higher level connection between the planner and other modules, further deductions could be made without extra computation power. We collect our work under these ideas in the Semi Qualitative World Model (SQWM).

TABLE I
SECTION TRANSITION TABLE

	1	2	3	4	5	6
1			X			X
2						
3	X			X		
4			X			X
5						
6	X			X		

A. *Field Representation*

The model starts with the field representation. The field is divided into six sections each uniquely numbered. Number of sections is arbitrarily chosen to be six. This number may be increased or decreased with further considerations.

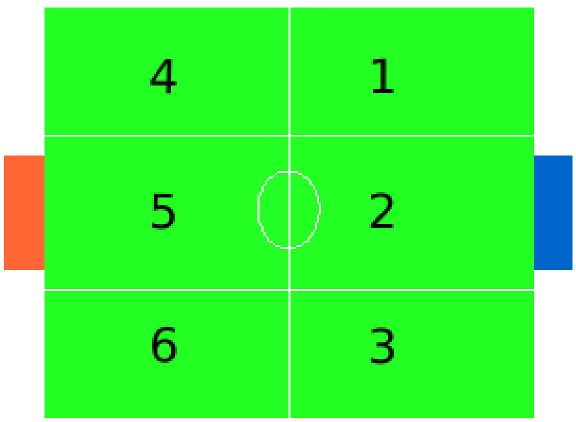

Fig. 1. Field Representation

Using this representation provides some interesting features which simplify other processes even without any further processing. As seen in the Section Transition Table, some transitions are impossible in the continuous and finite environment of the robot soccer. Such transitions are marked with a "X". One example is moving from the first section to the sixth section, which is not possible since robot has to be present in either 2nd, 4th or 5th section before arriving to sixth section. Therefore it is impossible to travel to section six from section one in one step.

Using these properties of the Field Representation, we can improve even the random chance of the localization algorithm. If we do not consider the X markings, random chance of guessing the right transition of the robot in the field is $\frac{1}{36}$ or 2.7%. If we consider X markings, then the random chance of guessing the right transition increases to $\frac{1}{28}$ or 3.6%. Although this seems to be a minor increase in random chance, the actual benefit lies in using the heading information, shown in figure 2 in order to increase the X markings.

An improvement to the Field Representation is generating the heading information, which also has similar properties to the section transitions. Heading can not also change discontinuously and more importantly heading information enables us to generate new X marked transitions to increase the random change of guessing the right transition.

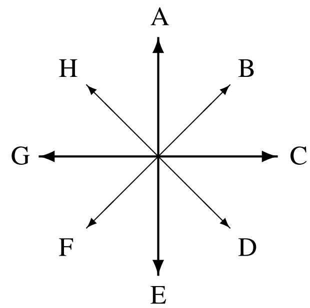

Fig. 2. Heading representation

Heading information among the Field Representation is used as follows:

In each section, there are six possible heading values, represented by the letters A-H. Here are a few examples indicating the directions of the headings: When the robot is in the second section and directly looking at the orange goal, heading A points towards the left of the field, directly looking at the orange goal. Heading E points toward the first section when the robot is in forth section perpendicular to the mid field line.

We can increase the number of X marked transitions greatly using the heading information, as in figure 3. For example even if the robot is in section 1, it can not move to section 4, unless it moves backwards, which is generally not the case.

Using the table shown in figure 3 it is possible to improve the random chance of guessing the right transition even further:

$$\frac{Number of X marked transitions}{Total possible transitions} = \frac{98}{288} = 34\%$$

As seen in the equation above, it is easier to reason and provide some means of complexity reduction even with only the representation itself with the use of higher level representations.

B. *Ball, beacon, goal, player representations*

Given the field representation and fuzzy logic processing methods, it will be sufficient to represent all other objects of the game to produce intelligent behavior.

Some of the other key-value pairs, which may be of value to the fuzzy decision process are:

1) Role of the robot (ie. goalie, attacker).
2) Current role of the robot.
3) Position of the robot in terms of the field representation.
4) Position of the ball in terms of the field representation.
5) Relative fuzzy positions of the beacons on the field.

6) Relative fuzzy positions of the goals on the field.

SQWM is not a finalized representation yet, further development should be expected.

V. Test Setup

Available Cerberus Team code has been modified to serve as a basis to the experiments. Although it takes quite a bit of time and effort, such a test bed is a must to be able to present a working method. Major modifications are introduced below.

In the actual Cerberus Team code, each role is represented with a finite state machine (FSM). As the state changes, different actions are performed. Actions provide different lower level behaviors, such as *searching for the goal* or *searching for the ball*. Each action is separate from each other. In other words each action is an atomic process, which can not be intervened with any other action. Only the higher level FSM can stop an action and start another as the global state of the robot changes, at certain points of execution of the action.

The term *action* is an abstraction to motor commands. Primary objective of each action is to generate a set of motor commands in order to perform the next step of relevant higher level action. Using this definition, it is quite appropriate to use atomic actions. However, this definition fails to address the uncertainty of the environment, which is one of the main titles of robotics.

A. Fuzzy command

This paper proposes a type-2 fuzzy approach to add a handle of uncertainty to this definition. In order to accomplish this, we needed to intervene the actions, which requires modifications to the Cerberus Team code.

Using the modifications made, it is possible to run all actions consequently and have the final motor control output only once at the end of one cycle. In other words this architecture presents the basis of a fuzzy construct within the existing Cerberus Team's planner.

The goal of this modification is to search for the best fitting type-1 fuzzy behavior, forming the primary membership function of the type-2 fuzzy system.

B. Statistics Package

To add the secondary membership function of the type-2 sets, a small statistics package will be implemented and used as a means of uncertainty handler. To compensate for the uncertainty involved in the input and output of the system, various statistical methods will be employed as the secondary membership function, to model the noise in the environment.

C. Performance measure

All tests will be judged with the frequently used metric of the Robocup domain, *goals scored per minute* in the same environment. The goal of the robot is to score a goal. Once a goal is scored, the ball is once more placed at a random point on the field. The robot scoring the highest in the goals per minute table wins the game.

The environment will be kept static, as dynamic environments will be setting new constraints, which would not be fair for each test. However, different static environment setups will be tried to test the planner more thoroughly.

VI. Conclusions and Future Work

As always there is more work to be done than that has been done. As it is the case in many research areas of robotics, there is yet no a *golden standard* for the planner architectures. Thus, the best available method of discovery is the educated trial and error method. Multiple methods will be tested with the presented test bed and results will be presented at CASE 2007 and online at [14]

A future work may be training the activation distributions with the Metrics for Game Evaluation introduced in [13]

Although SQWM will be open to alterations due to the requirements of current projects, it should be standardized accordingly to set criteria.

VII. Acknowledgments

The authors would like to thank Prof. Dr. Levent Akın, Cerberus Robocup Team Leader Çetin Meriçli and all the members of the Cerberus Team, Boğaziçi University AI Lab and İstanbul Bilgi University Computer Science Department for their kind and encouraging support.

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		1	2	3	4	5	6
1	1A		X	X	X	X	X
	1B			X	X	X	X
	1C			X	X	X	X
	1D			X			X
	1E		X	X		X	X
	1F		X	X		X	X
	1G		X	X	X	X	X
	1H		X	X	X	X	X
2		1	2	3	4	5	6
	2A	X		X	X	X	X
	2B	X			X	X	X
	2C	X			X	X	X
	2D	X			X		
	2E	X		X	X		X
	2F			X			X
	2G			X	X	X	X
	2H			X	X	X	X
3		1	2	3	4	5	6
	3A	X	X		X	X	X
	3B	X	X		X	X	X
	3C	X	X		X	X	X
	3D	X	X		X	X	
	3E	X	X		X	X	
	3F	X			X		
	3G	X			X	X	X
	3H	X			X	X	X
4		1	2	3	4	5	6
	4A		X	X		X	X
	4B			X			X
	4C	X	X	X			X
	4D	X	X	X			X
	4E	X	X	X		X	X
	4F	X	X	X		X	X
	4G	X	X	X		X	X
	4H		X	X		X	X
5		1	2	3	4	5	6
	5A	X		X	X		X
	5B	X			X		
	5C	X	X	X	X		
	5D	X	X	X	X		
	5E	X	X	X	X		X
	5F	X	X	X			X
	5G	X	X	X			X
	5H			X			X
6		1	2	3	4	5	6
	6A	X	X		X	X	
	6B	X	X		X	X	
	6C	X	X	X	X	X	
	6D	X	X	X	X	X	
	6E	X	X	X	X	X	
	6F	X	X	X	X		
	6G	X	X	X	X		
	6H	X			X		

Fig. 3. Section Transition Table using heading information